Pricing Dynamics of Multi-Product Retailers [1]

ABSTRACT

This paper attempts to broaden our understanding of retail pricing dynamics by providing some systematic evidence about U.S. grocery prices. Using a large data set containing information on twenty categories of goods from thirty U.S. metro areas for the period 1988-1997, we find a number of empirical regularities. Sales are common phenomenon in that retailers seem to have a "regular" price, and most deviations from that price are downward. There is also considerable heterogeneity in sale behavior across goods within a category, such as cereal. Within each category of goods, some items are regularly put on sale, while other items are rarely, if ever, put on sale. Finally, the probability of a sale on an item appears to be greater when demand for that item is higher. These results suggest that retailers use complicated strategies in pricing the items they sell that differ across items and over time. Studies that use retail prices and do not account for the process determining retail prices are likely to yield misleading results.

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I Introduction

The Federal Trade Commission and Department of Justice's antitrust division investigate mergers of competing firms to ensure that mergers that reduce consumer welfare are challenged or modified. In the past, both agency's staff had to rely almost exclusively on documentary evidence (e.g., marketing documents) or testimonial evidence (e.g. interviews with industry participants) to determine if the products produced by the merging parties were relatively close or distant substitutes. However, within the last five to ten years a tremendous amount of information on consumer prices and purchases (often in the form of scanner data) has become available to antitrust enforcers. The availability of this data has significantly changed the way economists approach certain types of merger investigations. For example, in consumer product industries, it is now possible to estimate demand systems to determine if products are close or distant substitutes. Alternatively, in some retail environments (see, for example, the expert reports in *FTC v. Staples/Office Depot*), it is possible to directly measure how different retailers constrain each other's pricing. In principle, the increased availability of highly disaggregated data should allow the antitrust agencies to better determine the substitutability of the products sold by the merging parties.

Despite the increase in the quantity of data available, there is relatively little research on how to correctly use this data to estimate economically meaningful measures of closeness between products or outlets. This lack of research creates a potentially serious problem for policy makers who would like to use the results from empirical studies to inform policy decisions. For example, often when competing consumer products companies merge, they will hire economists to conduct a statistical study showing the degree of substitutability across a group of products, including those of the merging firms. These studies typically use retail scanner data collected at grocery stores, drug stores, or mass-merchandisers. Whether these substitution measures correspond to the measures of interest to policy-maker depends critically upon the source of price variation. As we show below, most of the variation in consumer prices used to estimate substitution patterns comes from items being placed on "sale" by the grocery chain, not from general changes in wholesale prices. Previous theoretical and empirical research suggests that if retailers place items on sale to, in part, intertemporally price discriminate, then the substitution measures estimated using contemporaneous price and quantity data in a demand model will not correspond to the substitution measures relevant to policy-makers.

Price measurement is also an important issue in evaluating retailing mergers. For example, suppose a researcher would like to exploit the wealth of data available from grocery store scanners, to measure how the "price" charged by a retailer is affected by competition from other retailers. Given that a typical grocery stores sells more than 20,000 distinct items, the question of how to construct the grocery store's "price" becomes important. One approach to measuring price would be to construct a bundle of products corresponding to a typical consumer's purchases. However, even this task is difficult because retailers pursue different pricing strategies for different types of goods. For example, because consumers are more aware of the prices of popular products (e.g., Tide or Cheerios), grocery stores have strong incentives to charge low prices on these items to maintain a low-price image. In contrast, consumers know relatively less about the prices of most unbranded products, giving retailers less of an incentive to charge low prices for these products. In addition, some retail products often move between relatively high everyday prices and low sale prices while other products are rarely offered on sale. We argue that popular products' prices are likely to be more strongly affected by retail competition than less popular items, and that changes in retail competition may manifest themselves primarily in changes in the pricing of popular products.

The goal of this paper is to provide systematic evidence about grocery pricing behavior, and offer guidance to future researchers on how to use retail prices to both correctly estimate demand systems and measure the competitive significance of competing retailers. For our empirical work, we use a large non-public data set obtained from the Bureau of Labor Statistics (BLS) which contains more than 350,000 monthly quotes on 20 categories of consumer products from 30 U.S. cities. We use this data set to establish a number of pricing regularities. For instance, we find that most products have a regular retail price, and that most deviations from that price are downward, likely the result of sales.

We have also analyzed why retailers pursue different pricing strategies for the different types of products they sell. In an earlier paper (Hosken, Matsa, and Reiffen), we derived a model which shows that, other things equal, retailers will place products that are more popular on sale more often. We find strong empirical results consistent with this prediction. First, we observe there is substantial heterogeneity in which grocery items are placed on sale. Within a product category, e.g., cereal, we find that some brands are quite likely to go on sale, while others almost never go on sale. Finally, we find that products that have known seasonal increases in demand are more likely to go on sale in periods of high demand than low demand.

II. Literature Review

Two key features of the supermarket industry are that each firm sells a large number of individual products and that the typical consumer purchases many individual products in each visit. Casual observation suggests that the pricing policies adopted by supermarkets differ across goods and vary over time for each good. Specifically, a typical pattern is for a supermarket to put a group of products on sale each week and to advertise those prices, with the advertised products changing from week to week. The question of why there are temporary price reductions - that is, why retailers' profit-maximizing prices change over time - inherently must be analyzed in a dynamic setting. In contrast, the question of why the prices of a subset of goods are advertised can be analyzed in a static setting. Section A presents theories of dynamic pricing, while section B focuses on the static question of why multiple products are put on sale each period. Section C summarizes the relevance of the theoretical work to empirical studies that use retail prices.

A. Theories of Pricing Dynamics.

Previous research provides two types of explanations for the sales phenomenon. First, Conlisk, Gerstner, and Sobel have suggested that sales can be used to price discriminate between consumers based on differences in both their demand elasticity and their willingness to wait (which is analytically similar to differences in costs of inventorying). In their model, sales arise because periodic price reductions lead to a large volume of purchases by high-elasticity customers. Hence, this strategy allows the firm to charge a low price to high-elasticity customers, while most of the purchases by low-elasticity customers are at a high price.[2] Second, Varian has suggested that sales arise because consumers differ in their willingness to shop, and retailers compete for those consumers who will only buy at store with the lowest prices. The only symmetric equilibria in Varian's model feature mixed strategies, where all retailers choose their price from an identical continuous distribution.

Sobel combines elements of the two preceding models to explain sales. In his model, there are multiple retailers, and high-value consumers are not only willing to pay more for the good and less willing to wait (as in Conlisk, Gerstner, and Sobel), but they also are loyal to one retailer (as in Varian).[3] The basic characteristics of the equilibrium in Sobel's model resembles the equilibrium in the Conlisk, Gerstner, and Sobel model. Retailers charge a high price when the number of non-loyal customers is small, but as the number grows, it eventually becomes profitable to reduce price to attract non-loyal customers. The key difference between the monopoly and multiple retailer equilibria is that competing retailers will consider having a sale sooner than a monopolist.[4] Another difference is that "sale" prices are lower in the Sobel model. Finally, one can extend the model to show that the difference between the monopoly and multiple retailer cases is a general one. That is, a reduction in the number of competing retailers reduces the frequency and depth of sales, *but does not affect the non-sale price of any good*.

Hosken and Reiffen extend the Sobel analysis by considering competition between multi-product retailers. An implication of their model is that competition between retailers always leads to some goods being on sale in each period, while others will be at their "regular" price. Because any individual good will only be on sale infrequently, the identity of the goods sold at low prices changes from period to period.

B. Costly Information and Multi-product Retailers.

The literature on the price promotion of multi-product retailers tends to focus on the information value of the advertising. A contribution that is particularly relevant in the supermarket context is the work of Lal and Matutes ([1989], [1994]), who model competition between multi-product retailers. The main question that Lal and Matutes focus on is whether retailers charge the same markups on all items they sell. They show that (under certain circumstances, particularly when the retailers' advertising costs and the consumers' transportation costs are not too trivial or too great) retailers will charge relatively low markups on advertised items and large markups on unadvertised items.[5] Thus, their paper provides an economic explanation for the "loss leader" strategy used by many retailers.

Hosken, Matsa, and Reiffen extend the Lal and Matutes model to consider how retailers decide which products to advertise. They show that, other things equal, products that are relatively more popular (that is, are consumed by a higher fraction of the population), are more likely to go on sale. The intuition behind the result is that when advertising is costly, a retailer is going to try to reach the largest number of consumers at the lowest cost. Thus, by advertising a low price on a more popular item, the retailer attracts a large number of consumers who will also buy unadvertised items with relatively high margins.

While the theories we have summarized are highly stylized, they do yield a number of predictions we can examine in the data. For instance, the intertemporal price discrimination models of Sobel and Conlisk, Gerstner, and Sobel, predict that retail prices of certain kinds of products will normally be at a high everyday price and periodically be discounted to a low sale price. Hosken and Reiffen's multiproduct retailer model explains why retailers vary the products they put on sale over time, in particular, products for which intertemporal price discrimination is not a plausible explanation for sales, (e.g., products that cannot be inventoried like lettuce or bananas). Finally an extension of the Lal and Matutes model predicts that competing firms will be more likely to place popular products on sale than unpopular products. The empirical analysis in Section IV of the paper shows that these predictions appear to hold in the empirical distribution of prices.

III. Data

Many researchers estimating demand functions for specific consumer products use retail scanner data available from firms such as A.C. Nielsen. The information these firms can provide is quite detailed. For example, Nielsen sells price and quantity data as disaggregated as the weekly price and quantities of a particular stock keeping unit (or sku), e.g., an 18 ounce container of Skippy Creamy peanut butter, in a specific city. However, as a practical matter, gaining access to a broad set of products for a long time period is prohibitively expensive for most researchers. In this study, we make use of a data set provided to us by the Bureau of Labor Statistics (BLS). While this data set does not contain the specific brand information that data from a firm such as A.C. Nielsen provides, this data set contains a wide range of product prices for from many cities for a ten year time period, and was provided to us at no cost.

In collecting the data used to calculate the Consumer Price Index (CPI), the BLS collects prices on from a large number of retailers in 88 geographic areas, collecting prices of specific items in up to 94 categories of goods.[6] The goal of the BLS is to accurately measure changes in the prices consumers face. For this reason the BLS uses a sampling scheme that collects product prices that approximate consumer expenditure patterns. In addition, because this data is used to measure price movements over time, the BLS takes great pains to accurately measure the price of specific products over time. Thus, the underlying price quote data used in the construction of the CPI will allow us to observe how prices vary over time. Below, we describe in detail how the BLS collects its price data.

Within each product category, the BLS samples the price of a specific item at the same store monthly for up to 5 years. That is, if in the first month the BLS uses a 2-liter bottle of Pepsi as its cola product in a specific store, then it will continue collecting pricing data on 2-liter bottles of Pepsi as its cola item as long as the store remains in the sample and 2-liters bottles of Pepsi remain on its shelf. The number of retailers sampled in each area increases with the area's population. In each geographic area the BLS changes all of the stores in its sample every five years. Hence, the largest potential number of observations in any individual price series is 60. The choice of which specific item(s) in a category to sample from each supermarket is based on a revenue weighted-average randomization. For example, if 2-liter bottles of Pepsi represent 10% of a store's cola revenue, then the BLS randomization results in a 10% chance that 2-liter Pepsi will be the sampled cola product.

The data we use in this study consist of individual price series for specific products. For example, each price series in the cola category in Chicago contains monthly observations on the price of a specific brand and container size of cola at a retail outlet in the Chicago area, for up to 60 consecutive months. Most product categories have multiple price series in each geographic area. Unfortunately, the price series provided to us do not contain information that identifies the specific product and package size sampled within each category.[7] We only know that all of the prices within a price series correspond to prices for a specific product at a specific store within a category. We do not know, for example, whether that specific cola product is a 12-pack of Coke or a 2-liter bottle of Pepsi. We also cannot identify the store or chain associated with each price series. Hence, we cannot determine when two series are taken from the same store or chain.[8]

The data set we received from the BLS contains all of the price series the BLS collected on 20 categories of goods (see Table 2 for a list of the specific categories) from 30 geographic areas (see Table 3 for a list of the specific areas) for the period 1988-1997.[9] Tables 1-4 provide descriptive information about the data set.[10] Table 1 shows that the observations are fairly evenly distributed throughout the sample period, although some years have more observations than others. Table 2 presents both the number of unique price series and the number of observations for each product category. Our data contain far more information on some grocery products (e.g. ground beef and white bread) than others (e.g. baby food and paper products). This reflects a policy on the part of the BLS to collect more data on products that are viewed as more important in measuring the CPI. Table 3 shows the number of price series and items by geographic area. The sample contains much more information from larger population areas than smaller areas.

Table 4 presents a frequency distribution of the length of the individual price series by category. As discussed earlier, under the BLS sampling scheme, an individual price series can be as long as 5 years. However, as seen in Table 4, only a small fraction of price series in our sample are 5 years long.[11] In fact, most of the price series are less than 2 years in length for all product categories except ground beef, eggs, orange juice, and lettuce. According to the BLS, there are two reasons why many of our price series have relatively short lengths. The first reason is that we obtained the same ten calendar years (1988-97) of data for all cities. Because the BLS changes its sample of stores for 20% of its cities each year, 80% of the observations in the first year of our data are part of a series that began in a previous year. Hence, 80% of the observations for 1988 will be part of a price series that began outside of our sample period. Similarly, 80% of the observation for 1997 will be part of a price series that will conclude outside of our sample period. This means that for the 80% of 1988 observations that are parts of price series that began before 1988, the maximum series length will be 48 months, and for 60% of the observations the maximum series length will be 36 months, etc.

The second reason is that if the BLS surveyor arrives at the store and cannot find the exact product and package size of a particular item, she selects a new product in that category and creates a new price series. In the data set, it appears this is the primary reason why most of the price series are so short. For some of the product categories, e.g. canned soup or frozen dinners, this explanation seems plausible. These product categories have many different individual brands and package sizes, and it seems reasonable to believe that the life span of a randomly selected product is short. However, for more stable categories, e.g. cola drinks, we find this explanation less credible. The two leading brands of cola (Coke and Pepsi) come in four different varieties (the permutations of with, and without, sugar and caffeine) that were on the market with a commanding market share throughout the sample period. It seems unlikely that changes in the product mix would result in 40% of the price series for cola drinks being less than one year in length. The unexpectedly short duration of many of the individual price series appears to be the major shortcoming of the BLS data set. However, while the short length of some of our price series weakens our ability to detect price changes, it should not induce any bias into our analysis.

One final weakness with the data that might affect our ability to detect sales is that prices are sampled monthly, whereas previous research suggests that sales last either one or two weeks and the ideal frequency of observation is weekly (See Hosken and Reiffen, or Pesendorfer). In a large sample, this should not affect the proportion of our observations that are sales, but it will reduce our ability to detect sales. The reason that sales are more difficult to observe is only partially due to the reduced number of observations. A more fundamental problem arising from having less-frequent observations is that the retailer's costs are more likely to change between observations than if the data were weekly. Thus, some of the price movements we detect may reflect wholesale price changes rather than sales.

IV. Empirical Methods and Results

The purpose of this study is to identify some pricing regularities and relate them to the theory described in section II.. In particular we wish to demonstrate the importance of sales, describe some of features of sale behavior, and examine the implications of this source of retail price variation on empirical studies that use retail prices.

First, we document the extent to which products in our data have a "regular" price. We do this by calculating how often an individual product's price is at its "typical" level. Specifically, we conduct the following calculation: we first divide the data set into individual price series for each calender year (e.g. the tenth price series for crackers in Chicago for 1996). Then, for each annual price series, we calculate the modal price. Finally, for each category we determine the frequency with which prices in each individual price series are equal to their modal values.

Table 5 presents summary statistics to characterize the extent to which products have a regular price. Specifically, it presents frequency distributions for each product category describing how often the prices in each individual time series are equal to their modal values for that year With the exception of eggs and lettuce, the products' prices are equal to their modal value at least 50% of the time. Furthermore, with the exception of eggs, lettuce, and bananas, more than 25% of products are at their modal prices at least *75%* of the time. This evidence shows that over the course of a year, in spite of both sales and wholesale price changes most products have a regular price and are priced at that level most of the time.

The second aspect of the sale phenomenon is evaluating what happens when price is not at its regular level. If sales are important, then we would expect that when prices are not at their regular level, they are significantly more likely to be below the regular price than above it. Hence, we test for sales by comparing the percentage of deviations from the modal price that are above versus below the mode for each type of product in our sample. This comparison demonstrates the relative importance of retail margin changes versus wholesale price changes in affecting retail prices. If retail prices only change as the result of permanent changes in wholesale prices, then we would expect the percentage of retail prices above the mode to be at least as large as the percentage of deviations below the mode.[12] Conversely, finding that when the price is not at its mode, it is generally below the mode suggests that retail price changes are primarily driven by retailer behavior.

As seen in Table 6, for every category, prices below the mode are much more likely to occur than prices above the mode. In each product category, the difference between the number of downward deviations from the mode is higher than the number of upward deviations by a statistically significant amount. Thus, the data suggest that sales are an important cause of retail price variation for a wide variety of goods sold by retailers. As discussed above, it is likely that this result would only be enhanced if we had data at weekly, rather than monthly, intervals.

In this paper we focus on differences in sale behavior across products. To examine these differences, we must first operationalize the idea of a sale as a significant temporary reduction in the price of a retail item. We do this by saying that a sale occurs if a product's price falls by some fixed amount in a given month and then rises by a similar amount in the next observed month .[13] Tables 7 and 8 present some general facts about the prevalence of sales in our sample. In Table 8, we see that the likelihood that an item is placed on sale varies widely across categories of products. For instance, the baby food products sampled almost never go on sale, while colas and crackers go on sale fairly frequently. We note that the two most perishable products, bananas and lettuce, appear to be the most likely to go on sale using our definition. However, this conclusion requires some caution, as some of the "sale" behavior we detect is likely due to the greater volatility of the underlying wholesale prices for these items resulting from seasonal variation in output.

There also appear to be variations in sale behavior across the U.S. To create our measure of the probability of observing a sale in each geographic region, we restricted our attention to the ten items sampled in each of the thirty regions in our data set.[14] To calculate the averages presented in Table 8, we first calculate the average probability of a sale for each of the ten product categories. We then take the simple average of those category probabilities to construct the probability of observing a sale in a region. The differences in sale behavior varies significantly across the U.S. For example, in the Miami area the probability of seeing a sale of at least 10% was about .05 versus .09 in Chicago area. Further, these cross-sectional differences in sale behavior seem to be robust to the exact sale definition used.

While the evidence presented thus far suggests that sales are an important cause of variation in retail prices, it is not clear that sales are an important cause of price variation for all retail products. For this reason, we examine whether some grocery items are more likely to go on sale than others in the same product category. Our measure turns on the observation that, within each category, sales would be equally likely on all products if products were randomly chosen to be put on sale. If that were true, then knowing whether a particular product went on sale in a given year would not help predict its frequency of sale in subsequent years. Thus, we wish to test the null hypothesis that the probability of observing a sale on a particular product in subsequent years is independent of whether that product was on sale in a base year. The alternative implied by the theory is that within each category, the same products (those that are more popular) will be repeatedly put on sale, so that the probability of observing a sale in subsequent years is higher for products that had a sale in the base year.

We test this hypothesis as follows. For every price series longer than 2 months, we record whether that price series experienced a sale during the first twelve months for which we have data. We then divide the sample into two parts: the first contains price series that have a sale in the first twelve months and the second contains those price series that do not have a sale. Within each product category we then calculate two conditional probabilities: the probability that a price series would experience a sale during the second year of the sample, conditional on the product being in the first group (i.e., having a sale within the first 12 months), and the probability of a sale in the second year conditional on being in the second group. We then test the null hypothesis that the conditional probability of observing a sale in the second 12-month period is the same for both groups. The results appear in Table 9.[15] For *every* product category in our sample the conditional probability of observing a sale is larger, often substantially larger, if the price series experienced a sale within the first 12 months. In fact, in 19 of the 20 hypotheses tests listed, we reject the null hypothesis with a z-statistic greater than 2.5.[16] For example, of the 62 cereal price series that experienced a sale of at least 10% within their first 12 months in the sample, 50.0% experienced at least one additional 10% sale in the second 12 months of the sample period, while only 18.6% of the 274 price series that did not experience a sale within the first 12 months experienced at least one 10% sale in the second 12 months. The difference in these conditional probabilities is different from zero at any conventional level of statistical significance (z=5.20). We interpret this as strong evidence that there is substantial heterogeneity across products in the likelihood of having a sale. Within categories, retailers appear to systematically place some products on sale more often than others. This result is robust across 20 large categories of goods, over time, across the U.S. and for five different definitions of sales (5%. 10%, 20%, and 25%, as well as the 15% reported here). Unfortunately, the BLS data does not allow us to relate product characteristics (e.g. a product's market share) to the probability of going on sale. However, the data suggest that products differ widely in the frequency with which they are put on sale.

This result is consistent with the prediction that more popular products (defined as those being consumed by a larger proportion of consumers) should go on sale more often. However, because we cannot know individual product identities in the BLS data, we do not know the relative popularity of products, and this result is a rather indirect test of this hypothesis. A somewhat more direct test takes advantage of the fact that some goods become more popular at certain times of the year. The theory predicts that as a product becomes more popular, it becomes more likely to be put on sale. The hypothesis we test is that in each of these categories, the frequency of sales rises during the high-demand period.

Of the twenty products in our sample, we identify five which have predictable seasonal increases in demand. The demand for soup increases in the fall and winter (October thru March), peanut butter demand increases as part of back to school planning in August and September, egg demand increases around Easter, and ground beef and hot dog demand increases during the summer barbeque season (June, July and August). Further, because the costs of producing these items are not seasonal, we are reasonably confident that any change in sale behavior is a result of retailers' reactions to changes in demand rather than supply. The results of these tests are presented in Table 10. The results strongly support the theoretical analysis. We see for both of the sale definitions we consider, retailers are more likely to put these items on sale in periods of high demand, and that these differences are statistically significant in virtually all cases at any conventional significance level. Thus, our data suggests that retailers systematically *lower* the prices of items that experience increases in demand. While these results are not surprising to anyone who shops in a grocery store, the analysis presented here provides an explanation for this phenomenon: A retailer attracts a consumer by offering more consumer surplus than its rival. Because it is costly for a retailer to inform consumers of the price of any individual item, other things equal, the least costly way for retailers to assure a given level of surplus to the largest number of consumers is to put items on sale that are attractive to the widest audience possible. Hence, when products have known upward spikes in demand, we would expect retailers to find it more attractive to put these items on sale.

Using the BLS data we have seen that products appear to have a regular price and that most deviations from that price appear to be sales. There is also substantial heterogeneity across products in the likelihood a retailer puts the product on sale. Within each product category, some products are far more likely to go on sale than others. Finally, we have seen some evidence that suggests products are more likely to be put on sale when they are more popular, e.g. eggs at Easter.

V. Discussion

As noted above, the increased availability of store and market-level retail pricing data has led to an increase in research based on that data. Two important strands of this research are product-specific demand elasticity studies, and studies of the relationship between retail market structure and pricing. Our analysis of the BLS price data yields some important insights into retail pricing behavior that affect the interpretation of the results of such research. Products appear to have a regular price level that is maintained through relatively long periods of time. Relatedly, a subset of products are periodically temporarily discounted from this everyday price. These temporary discounts; i.e., sales, are an important component of retail price variation, and are typically retailer specific. [17] The fact that retailers are not setting prices by simply charging a fixed markup on their wholesale costs has implications for studies that wish to use retail prices to estimate demand elasticities for consumer products for at least two reasons.

The first reason relates to correctly measuring the prices and quantities used in studies that measure consumer demand elasticities. Most of the studies submitted to the FTC (either by the merging parties or interested third parties) that we have reviewed used highly aggregated price and quantity data (either for a region, such as the northeastern U.S., or a metropolitan area). However, because retailers within a market will often be charging different prices for the same item in a market at a point in time (e.g., if one retailer is offering the item on sale), the average price charged in a market for an item will be a poor measure of the actual price consumers face. Thus, to avoid this type of measurement error, a researcher should collect the price and quantity data for consumer products at the level of the specific retailers in a city.[18]

Unfortunately, there are also problems with using retailer-specific price and quantity data. For example, if many consumers choose to buy a specific item at the lowest price retailer in the city, then a retailer having a sale on that item (e.g. gallons of milk) may see its sales of that product surge, even though sales for the item in that city are barely affected. In this case, using retailer specific data can result in elasticities being overestimated.[19] While both types of data have measurement problems, the prudent approach by researchers would be to use both types of data in a study to check the robustness of their results.

The second, and more problematic reason results from retailers using sales to both compete with one another and to intertemporally price discriminate. As discussed earlier, Sobel, Pesendorfer and Hosken and Reiffen each develop models that show that retailers who are selling goods that can be inventoried by consumers (e.g. non-perishable goods), have incentives to charge different prices over time to price discriminate against consumers who have high inventory costs. In these models, in each period in which the retailer does not have a sale, the demand curve for the next period shifts further to the right. Thus, the strategic behavior by the retailer in period t affects the level of the demand curve in period t+1. Existing empirical evidence suggests that retailers are currently engaging in such price discrimination, validating our concern. For example, in Pesendorfer's study of the demand for ketchup he finds that the current period demand for ketchup is a function of lagged prices. In addition, it is well known that retailers sell very large quantities during sales that would imply unrealistic demand elasticities in the absence of these consumer inventory effects.[20]

When intertemporal price discrimination by retailers is an important source of retail price variation, the elasticities calculated using contemporaneous price and quantity data measure how much observed purchasing increases when a store has a sale, not what the level of purchases in a time period would be if the retail price of the item *permanently* lowered its price to a given level. In order to determine if a merged firm has an incentive to increase price following a merger, a researcher needs to know how consumers would respond to a permanent change in the price distribution (everyday price, sale price, and frequency of sale) of a good. It is for this reason that the demand elasticities estimated using contemporaneous price and quantity data provide limited information to policy makers.

There are similar problems in using retail prices to measure the effect of competition between retailers. Retailers use different strategies to price the different items they sell. For example, grocery chains report that consumers are very sensitive to the prices charged for the most popular products they sell (e.g. leading brands like Tide or Cheerios, or frequently purchased non-branded products like milk and ground beef). Because these products are frequently purchased by consumers and sold by a large number of retailers, consumers have a good sense of what the rival retailers typically charge for these items. For example, grocery store operators try to very closely peg their prices on these "price sensitive" items to their rivals in order to maintain their price image in a market. If a grocery chain's milk prices deviate from their typical level, the chain stands to lose significant business. In contrast, consumers are less aware of the prices of items they purchases less frequently (e.g. pancake mix or canned corn). Consequently, retailers face less of a penalty if their prices on these items are relatively high. These strategies appear to carry over to a retailer's decision of which items to put on sale. As discussed earlier, by offering consumers a sale, retailers commit to offering consumers low prices on a set of items. Because advertising a sale is costly, retailers want to advertise the items that are most likely to attract consumers to the store; that is, retailers will advertise relatively popular items.

Because retailers pursue different pricing strategies for different kinds of goods, we believe that the (quantity-weighted) average price of a bundle containing all goods sold by a supermarket is unlikely to be the most useful tool for evaluating competition. Retailers face the strongest incentives to lower prices on the products that will bring them the most customers. Thus, we expect that the price of popular, frequently purchased, items would be most affected by retail competition. Similarly, competition may also manifest itself through the type of sales retailers offer consumers (how many items, depth of discounts) in addition to the everyday price level. Recall, in Sobel's model of retailer competition, the number of rivals in a market does not affect the "everyday" price, it only affects the frequency of sale and depth of sale. Further, because consumers appear to anticipate sales, a disproportionate number of consumer purchases take place during sales. Thus, the consumers who may be harmed by a merger (the removal of a rival from a market) may not be the consumers who purchase at the everyday price, but the price sensitive consumers who time their purchases to coincide with sales.

For these reasons, we recommend that researchers analyze the frequency and depth of sales to measure the effects of competition (or changes in competition). Further, when examining price levels, researchers are more likely to observe the effects of retail price competition on the most popular items retailers sell.

VI. Conclusions

Food retailers adjust their prices in ways that are often bewildering to economists.

This paper attempts to broaden our understanding of retail pricing dynamics by providing some systematic evidence about U.S. grocery prices. Using a large data set containing information on twenty categories of goods from thirty U.S. metro areas for the period 1988-1997, we find a number of empirical regularities. First, for each of twenty categories of goods in our BLS sample, stores seem to have a "regular" price, and most deviations from that price are downward. Second, we find there is considerable heterogeneity in sale behavior across goods in each category; within each category of goods, the same items are regularly put on sale, while other items are rarely, if ever, put on sale. Third, the probability of a sale on an item appears to be greatest when demand for that item is highest.

While many aspects of retailer behavior are beyond the scope of this paper, our data do reveal some patterns in their decision-making. For example, retailers appear to pursue different pricing strategies for different grocery items. In particular, it appears that more popular products are more likely to go on sale. In addition, the evidence we have found is consistent with models that predict retailers will periodically offer items at a reduced price to intertemporally price discriminate against consumers with high inventory costs. These results suggest that retailers do not play a passive role in bringing final goods to market (e.g., simply marking up the price of all goods they sell a fixed amount or percentage).

This observation has important implications for interpreting results based on retail pricing data. For instance, most of the variation in retail prices that is used to identify elasticities in studies of demand for specific consumer products will be the result of retail sale behavior, not changes in wholesale costs. If retailers are using sales to intertemporally price discriminate, then these estimated demand elasticities will not measure the true relationship between consumer prices and *consumption*, but will instead measure how consumer *purchases* change in response to predictable short term decreases in retail prices. The elasticity that is of interest to policy makers (how much consumer consumption will fall if all prices increase) requires the researcher to observe a shift in the entire distribution of consumer prices, sale and non-sale, (such as would occur following a changes in wholesale prices). Similarly, studies that use retail prices to measure the relationship between consumer prices and competition should be careful in choosing which retail prices to analyze. For example, in Sobel's model changes in the number of market participants only affect product's sale prices, not their everyday prices. Thus, if only popular items go on sale, it is conceivable that only popular items will be affected by changes in the level of competition.

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Table 1: Description of Data Set
by Year

Year	Proportion of Observations
1988	11.4%
1989	10.0%
1990	9.6%
1991	9.9%
1992	10.1%
1993	9.2%
1994	9.3%
1995	10.3%
1996	9.8%
1997	10.4%

Table 2: Description of Data Set By Product

Product	Number of Price Series	Number of Observations
Baby Food	299	6579
Bananas	1142	26284
Canned Soup	1310	26480
Cereal	1631	26603
Cheese	1233	27183
Snacks	1288	21654
Cola Drinks	1116	19343
Cookies	750	14125
Crackers	311	6982
Eggs	905	27915
Frozen Dinners	561	7561
Frozen Orange Juice	491	13703
Ground Beef	909	27551
Hotdogs	471	9594
Lettuce	672	25687
Margarine	477	11826
Paper Products	620	7018
Peanut Butter	342	9188
Soap and Detergents	820	10158
White Bread	1043	24663
Total	16391	350097

Table3: Descriptive of Data by Region

Region	Number of Price Series	Number of Observations
Atlanta	361	6547
Boston	570	11022
Buffalo	317	5866
Chicago	1765	40019
Cleveland	492	9730
Dallas	536	10657
Dayton	289	6733
Denver	341	6231
Detroit	1069	21404
El Paso	323	7312
Greater Los Angeles	557	15682
Jacksonville	297	7118
Kansas City	374	6033
Los Angeles	1694	35487
Miami	387	7116
Minneapolis	337	6379
New Orleans	375	6812
Suburbs of New York City	685	17816
Philadelphia	830	17270
Portland	289	5565
Richmond	385	8102
St. Louis	654	13530
San Diego	331	5556
San Francisco	947	25186

Scranton	335	6752
Seattle	355	6566
Syracuse	311	8577
Tampa	280	5515
Tucson	369	7658
Washington, D.C.	536	11856
Total	16391	350097

Table 4: Sample Description:
Frequency Distribution of Length of Time Series

	Less than 1 year	1 to 2 years	2 to 3 years	3 to 4 years	4 to 5 years	5 years or more
All Products	37.8%	24.4%	15.7%	10.1%	8.8%	3.2%
Baby Food	44.1%	17.4%	16.1%	11.0%	7.4%	4.0%
Bananas	23.6%	28.4%	26.4%	21.5%	0.1%	0%
Canned Soup	37.3%	30.5%	12.7%	9.1%	7.9%	2.5%
Cereal	51.5%	24.5%	10.1%	7.2%	5.2%	1.5%
Cheese	37.0%	23.1%	16.4%	8.7%	11.3%	3.5%
Snacks	45.3%	28.3%	12.8%	8.4%	4.7%	0.5%
Cola Drinks	40.9%	25.7%	21.1%	10.8%	1.5%	0%
Cookies	43.9%	24.2%	15.1%	6.5%	7.8%	2.5%
Crackers	31.2%	28.6%	18.0%	9.3%	10.6%	2.3%
Eggs	19.0%	23.2%	16.3%	13.2%	19.5%	8.8%
Frozen Dinners	56.7%	24.4%	11.8%	4.8%	2.1%	0.2%
Frozen Orange Juice	26.5%	20.3%	16.7%	14.5%	15.1%	6.9%
Ground Beef	19.0%	23.4%	17.8%	13.5%	18.3%	8.0%
Hotdogs	40.3%	22.5%	18.1%	8.7%	8.9%	1.5%
Lettuce	6.8%	17.9%	19.1%	15.4%	27.7%	13.1%
Margarine	32.1%	24.3%	14.2%	9.3%	15.9%	4.2%
Paper Products	64.4%	22.2%	9.4%	2.0%	0.9%	0.6%
Peanut Butter	28.4%	16.0%	22.6%	13.1%	13.2%	6.7%
Soap and Detergents	61.0%	23.6%	9.4%	2.2%	3.1%	0.6%
White Bread	34.6%	21.8%	17.4%	10.6%	11.8%	3.8%

Table 5: Summary of Frequency Distributions of

How Often Price Quotes are at Their Modal Value

Product	Percent of Time Series at Modal Price less than 25% of Time	Percent of Time Series at Modal Price less than 50% of Time	Percent of Time Series at Modal Price more than 75% of Ti me	Annual Price Series
Baby Food	0.3%	10.1%	50.2%	745
Bananas	1.1%	31.4%	23.0%	3055
Canned Soup	0.1%	15.0%	43.5%	3231
Cereal	0.4%	16.6%	44.0%	3366
Cheese	0.7%	21.4%	42.7%	3138
Snacks	0.1%	9.9%	54.1%	2832
Cola Drinks	1.4%	25.7%	42.3%	2444
Cookies	0.4%	14.6%	53.4%	1744
Crackers	0.4%	20.3%	37.7%	799
Eggs	16.9%	63.4%	15.6%	2877
Frozen Dinners	0.1%	13.4%	51.7%	1109
Frozen Orange Juice	1.2%	27.7%	29.4%	1463
Ground Beef	0.8%	28.7%	32.1%	2848
Hot Dogs	0.8%	24.6%	41.8%	1116
Lettuce	73.2%	84.6%	2.3%	2563
Margarine	0.9%	24.6%	39.2%	1300
Paper Products	0.5%	12.7%	49.1%	1312
Peanut Butter	0.3%	21.1%	38.1%	990
Soap and Detergent	0.6%	11.2%	52.2%	1889

White Bread	0.4%	16.5%	47.4%	2787

Table 6: Percentage of Prices Above and Below the Annual Modal Price By Product

	Percentage Above Mode[i]	Percentage Below Mode[i]	Z-Statistic[ii] (P value)
Baby Food	9.5 (592)	16.6 (1032)	3.95 (.0000)
Bananas	14.0 (3371)	28.2 (6791)	15.88 (.0000)
Canned Soup	10.5 (2615)	20.3 (5043)	10.81 (.0000)
Cereal	11.6 (2885)	20.3 (5038)	9.85 (.0000)
Cheese	12.8 (3238)	19.7 (4986)	8.15 (.0000)
Snacks	7.0 (1453)	17.2 (3581)	9.40 (.0000)
Cola Drinks	10.5 (1872)	23.5 (4184)	11.80 (.0000)
Cookies	7.8 (1049)	18.6 (2491)	8.09 (.0000)
Crackers	7.8 (516)	25.7 (1699)	8.66 (.0000)
Eggs	25.6 (5795)	32.4 (7346)	8.55 (.0000)
Frozen Dinners	7.8 (552)	21.6 (1531)	7.24 (.0000)
Frozen Orange Juice	12.3 (1560)	27.5 (3479)	11.86 (0000)
Ground Beef	11.8 (2996)	25.6 (6480)	15.22 (0000)
Hotdogs	10.2 (908)	24.3 (2170)	8.92 (0000)

Lettuce	18.2 (4206)	65.0 (15007)	53.84 (0000)
Margarine	11.1 (1222)	23.4 (2576)	8.95 (0000)
Paper Products	9.2 (602)	22.3 (1454)	6.94 (0000)
Peanut Butter	11.5 (984)	22.2 (1904)	7.03 (0000)
Soap and Detergents	8.7 (832)	20.8 (1996)	7.79 (0000)
White Bread	10.6 (2462)	18.0 (4183)	8.11 (0000)

i Number of observations in parentheses.
ii P-Values in parentheses.

Table 7: Probability of Sale by Product Category

	Observations	5% Sale	10% Sale	15% Sale	20% Sale	25% Sale
Baby Food	5670	0.0219	0.0144	0.0083	0.0048	0.0025
Cereal	22193	0.0463	0.0303	0.0232	0.0179	0.0134
Canned Soup	22655	0.0516	0.0347	0.0235	0.0155	0.0104
Peanut Butter	8197	0.0661	0.0378	0.0221	0.0138	0.0083
Cheese	23227	0.0619	0.0449	0.0215	0.0223	0.0133
White Bread	21247	0.0585	0.0511	0.0392	0.0291	0.0204
Soap and Detergent	4180	0.0730	0.0522	0.0349	0.0239	0.0144
Paper Products	2936	0.0811	0.0586	0.0351	0.0191	0.0116
Margarine	10415	0.0825	0.0587	0.0396	0.0293	0.0204
Cookies	11844	0.0881	0.0628	0.0382	0.0237	0.0141
Eggs	25009	0.1111	0.0648	0.0366	0.0263	0.0197
Snacks	17596	0.0802	0.0684	0.0551	0.0451	0.0299
Frozen Orange Juice	12175	0.0881	0.0702	0.0536	0.0447	0.0313
Ground Beef	24946	0.1080	0.0711	0.0476	0.0322	0.0208
Frozen Dinner	5834	0.0921	0.0754	0.0614	0.0425	0.0255
Hot Dogs	8053	0.0929	0.0777	0.0596	0.0468	0.0340
Cola	16581	0.0977	0.0794	0.0589	0.0431	0.0286
Crackers	5989	0.1186	0.0945	0.0725	0.0533	0.0359
Bananas	23306	0.1455	0.1378	0.1160	0.0983	0.0826
Lettuce	23101	0.2321	0.1896	0.1523	0.1224	0.0967
For All Products	295154	0.0959	0.0736	0.0547	0.418	0.0306

Table 8: Probability of Sale by Region

Region	Observations	5% Sale	10% Sale	15% Sale	20% Sale	25% Sale
Atlanta	3759	0.0922	0.0697	0.0505	0.0368	0.0257
Boston	7475	0.0942	0.0750	0.0596	0.0468	0.0357
Buffalo	3547	0.0905	0.0680	0.0491	0.0401	0.0304
Chicago	25088	0.1134	0.0937	0.0725	0.0587	0.0451
Cleveland	6263	0.0976	0.0766	0.0583	0.0459	0.0357
Dallas	6715	0.0992	0.0754	0.0543	0.0429	0.0320
Dayton	4758	0.0817	0.0658	0.0510	0.0391	0.0288
Denver	3435	0.0979	0.0725	0.0559	0.0410	0.0340
Detroit	13406	0.0901	0.0710	0.0552	0.0438	0.0301
El Paso	5307	0.0878	0.0654	0.0490	0.0343	0.0245
Greater Los Angeles	9788	0.1067	0.0791	0.0581	0.0422	0.0323
Jacksonville	4513	0.0945	0.0700	0.0512	0.0438	0.0322
Kansas City	3705	0.1069	0.0842	0.0632	0.0478	0.0337
Los Angeles	22456	0.1040	0.0795	0.0598	0.0471	0.0364
Miami	4726	0.0683	0.0513	0.0372	0.0294	0.0198
Minneapolis	3419	0.0994	0.0715	0.0509	0.0359	0.0270
New Orleans	4053	0.0768	0.0559	0.0424	0.0292	0.0209
Suburbs of New York City	11716	0.0953	0.0749	0.0564	0.0427	0.0314
Philadelphia	10342	0.0960	0.0805	0.0649	0.0528	0.0383
Portland	38531	0.1145	0.0888	0.0717	0.0581	0.0465

Richmond	5127	0.1049	0.0859	0.0637	0.0482	0.0344
St. Louis	3408	0.0879	0.0672	0.0524	0.0423	0.0312
San Diego	15281	0.1083	0.0781	0.0579	0.0451	0.0328
San Francisco	4245	0.1117	0.0845	0.0620	0.0449	0.0319
Scranton	3717	0.0879	0.0687	0.0492	0.0335	0.0238
Seattle	7934	0.1068	0.0844	0.0677	0.0495	0.0381
Syracuse	5771	0.0979	0.0810	0.0670	0.0544	0.0412
Tampa	3376	0.0888	0.0625	0.0453	0.0337	0.0240
Tucson	5007	0.1185	0.0891	0.0603	0.0434	0.0330
Washington, D.C.	7671	0.0877	0.0639	0.0439	0.0333	0.0236

Table 9- Percent of Price Series Experiencing at Least One Sale of 15% or more in the Second Year, Conditional on Whether there is a Sale within the First Year

Product	Conditional On at Least One Sale within the First Year (number of price series)	Conditional on No Sale within the First Year (number of price series)	Z-Statistic (p-value)
Baby Food	80.0% (5)	2.2% (92)	7.04 (0)
Bananas	78.2% (367)	49.6% (121)	6.02 (0)
Canned Soup	43.4% (76)	13.7% (299)	5.81 (0)
Cereal	50.0% (62)	18.6% (274)	5.20 (0)
Cheese	51.9% (106)	14.8% (290)	7.56 (0)
Snacks	61.2% (103)	25.6% (172)	5.86 (0)
Cola Drinks	59.7% (124)	23.9% (155)	6.07 (0)
Cookies	69.8% (43)	16.3% (135)	6.71 (0)
Crackers	72.9% (48)	23.2% (56)	5.08 (0)
Eggs	49.7% (157)	23.3% (305)	5.75 (0)
Frozen Dinners	59.5% (42)	26.2% (42)	3.09 (.0022)
Frozen Orange Juice	62.8% (94)	28.5% (137)	5.18 (0)

Ground Beef	60.6% (175)	31.4% (287)	6.16 (0)
Hot Dogs	63.1% (65)	31.5% (74)	3.29 (.0012)
Lettuce	90.6% (383)	75.7% (74)	3.64 (.0002)
Margarine	64.3% (56)	25.2% (127)	5.04 (0)
Paper Products	66.7% (9)	35.9% (39)	1.69 (.0910)
Peanut Butter	32.3% (31)	7.8% (129)	3.70 (.0002)
Soap and Detergent	54.5% (22)	16.7% (42)	3.15 (.0016)
White Bread	54.2% (131)	15.0% (253)	8.07 (0)

Table 10: Probability of Sale for Various
Products in Relatively High and Low Periods of Demand
Sale = 15% reduction

Product/Percent Sale	Probability of Sale in High Demand Period	Probability of Sale in Low Demand Period	Z-Statistic for difference in Probability
Ground Beef	0.06422	0.04515	4.10
Hot Dogs	0.07245	0.05701	1.75
Eggs	0.06926	0.03529	2.78
Canned Soup	0.02677	0.01876	4.25
Peanut Butter	0.03228	0.01897	3.27

1. The opinions expressed in this paper are those of the authors and not necessarily the Federal Trade Commission or any of its individual Commissioners. We would like to thank Steve Scutt for his assistance in putting together the data set, and Sara Harkavy and Morgan Long for providing excellent research assistance. We would also like to thank Cindy Alexander, Jim Ferguson, Charles Thomas and Aileen Thompson for their helpful comments on previous drafts.

2. Lal and Matutes [1989] use a similar explanation for competing multi-product retailers using different (static) pricing strategies for their array of goods. In their model, each retailer has a low price on a different good, which causes low transportation cost consumers to buy at more than one store each period, but allows the retailers to charge high prices on some items to high transportation cost/high reservation value consumers. Banks and Moorthy [1999], show that coupons can be another way of offering low prices to low reservation price/low search cost customers, while maintaining high prices to high reservation price/high search cost consumers.

3. Pesendorfer generalizes Sobel's analysis by introducing a third type of consumer; store-loyal, but low-value.

4. In contrast to the monopoly retailer case, with competing retailers the probability that a sale may occur becomes positive as soon as the expected profit from selling to the accumulated low-value consumers at a low price equals the profit from selling to the loyal consumers at their higher reservation value.

5. In the Lal and Matutes model consumers realize that when they go shopping they will purchase a bundle of products (some advertised and some unadvertised) and choose the retailer (or retailers) that will sell them that bundle at the lowest cost. They understand that the unadvertised products will be sold at relatively high prices, and incorporate this information into their decision making process. In their model advertising is, in essence, a commitment device that keeps the retailer from charging the consumer high prices on all of his products once he has sunk the transportation costs of visiting the store.

6. A category is a fairly narrow classification of consumer goods, e.g. cola drinks, eggs, and white bread are BLS categories.

7. The BLS does maintain the information on the specific retailer and product surveyed, however, for confidentiality reasons they cannot release this data.

8. For this reason, we cannot use the BLS data to examine any implications regarding the relationship of prices movements on products within a store.

9. The BLS occasionally updates the sampling scheme it uses to collects consumer prices. We choose to collect data from the time period 1988-1997 because the BLS used the same sampling scheme throughout the time period.

10. The BLS imputes prices for missing values. However, because the goal of our study was to study the way actual consumer prices changed over time, we deleted all of the imputed prices from our data set, roughly 5% of the observations.

11. Some of the price series have lengths longer than 5 years because the BLS collected an additional year of data for the regions that were rotated out in 1997 for the update of the CPI.

12. Given there is upward trend to pricing due to inflation, other things equal we would expect most wholesale price changes to be increases in price. Implicitly in this analysis, we assume there is no systematic pattern in wholesale price changes, e.g. manufacturers changing prices every March.

13. We consider five different levels of price reductions in our definition of a sale, discounts of at least - 5%, 10%, 15%, 20%, and 25%.

14. The products included are bananas, canned soup, cereal, cheese, chips, cola drinks, eggs, ground beef, lettuce, and white bread.

15. We consider the five different minimum price decreases in our sale definition (- 5%, 10%, 15%, 20%, and 25%). In the interest of brevity, only the results for the 15% definitions are presented here.

16. The corresponding number of z-statistics over 2.5 using all 5 sale definitions was 91 out of 100. Note that for some of the comparisons of conditional probabilities, the number of price series is very small. In these cases it is incorrect to assume that the difference in proportions is approximately normal, and instead we simply interpret the computed z-statistics as measures of the size of the difference between conditional probabilities.

17. While it is true that retailers often receive promotional allowances from manufacturers to subsidize a sale, our understanding is that these promotions are offered simultaneously to all retailers in a geographic area, and that the individual retailer decides how much of the promotional discount will be passed thru to consumers. In addition, Hosken and Reiffen, show that price changes across retailers are not correlated. The lack of correlation in changes in retailer prices suggests that individual retailers play an important role in both choosing the timing and depth of sales.

18. If demand curves are linear, this measurement problem should not be an issue, however, in general it would be.

19. This problem is probably not insurmountable. For example, by controlling for which firm has the lowest price on a particular item at a point in time (e.g. with an intercept shifter), it may be possible to control for this store switching effect.

20. For example, a study described by Progressive Grocer found that the quantity of soda sold increased between 600% and 800% and that the quantity of flour sold increased between 940% and 1800% during a sale.